Which types of workers populate the Italian labour market?

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Abstract

This paper investigates the role of worker heterogeneity in shaping labour market dynamics in Italy, with a particular focus on differences between migrants and natives. Building on the framework of Gregory et al. (2025), we classify workers into three latent types—α, β, and γ—that capture persistent differences in job-finding rates, employment stability, and earnings trajectories. Using longitudinal administrative data covering worker transitions between 2009 and 2020, we apply a grouped fixed-effects approach to identify these latent types and examine how their distribution varies across demographic and institutional dimensions. We assess whether migrants are disproportionately represented among the more unstable γ-type workers and how such composition effects amplify unemployment fluctuations. By linking empirical evidence to a search-theoretic model, the paper contributes to understanding how institutional dualism and migration interact to sustain inequality and employment instability in segmented labour markets.

Keywords: Labour market flows, transition probabilities, worker types, k-means.

JEL Classification: C18, C53, E32, E24, J6.

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1 Introduction

Understanding why unemployment responds so strongly and persistently to economic shocks remains one of the central questions in labour economics. Traditional search and matching models often assume that workers are homogeneous, but growing empirical evidence suggests that individuals differ markedly in their attachment to the labour market and in the stability of their employment relationships. These differences can have important implications for aggregate labour market dynamics and for the persistence of inequality across groups and over time.

Recent work by Gregory et al. (2025) provides a compelling demonstration of this idea. Using detailed administrative data from the United States, they show that workers' transitions across employment states can be effectively summarized by three latent types: α, β, and γ-that capture fundamental heterogeneity in job-finding rates, job stability, and earnings trajectories. α-workers find jobs quickly and retain them for long periods; γ-workers experience long unemployment spells and short job durations; and β-workers fall in between. Importantly, this heterogeneity cannot be explained by observable characteristics such as education, gender, or industry, suggesting that differences in workers' unobservable characteristics such as underlying match quality and search efficiency are key to understanding aggregate unemployment dynamics. Their analysis also shows that macroeconomic downturns disproportionately affect γ-workers, whose unstable employment amplifies and prolongs aggregate unemployment fluctuations.

This paper applies and extends their framework to the Italian labour market, using administrative data covering worker transitions between 2009 and 2020, with a particular focus on migrant workers. Italy offers a compelling context for replication and comparison with the U.S. case for at least two reasons.

First, the Italian labour market is structurally segmented and institutionally dualistic. Since the 1990s, a sequence of reforms aimed at increasing flexibility at the margin—most notably the Pacchetto Treu (1997), the Legge Biagi (2003), and the Jobs Act (2015)—has encouraged the diffusion of temporary, fixed-term, and agency contracts, while leaving the regulation of open-ended employment largely unchanged. The result has been a persistent coexistence of a core group of workers in stable, protected jobs and a large periphery of workers facing recurrent short-term contracts, frequent job interruptions, and weaker access to social insurance. This institutional dualism is likely to shape the heterogeneity in employment trajectories captured by the alpha–beta–gamma classification. In particular, the prevalence of short-term contracts and discontinuous employment spells may mechanically expand the share of "gamma-type" workers—those with unstable job attachment and high transition rates—relative to the U.S., where the baseline model was first developed. Furthermore, employment protection legislation in Italy remains highly asymmetric, favouring insiders and discouraging transitions from temporary to permanent jobs. As a consequence, heterogeneity in employment histories may reflect not only individual characteristics (such as productivity or search ability) but also institutional constraints on mobility.

Second, immigration has profoundly reshaped the Italian labour force over the last two decades. Migrants now represent around 10 percent of total employment, but their distribution across sectors and contract types is far from uniform. They are heavily concentrated in low-wage, low-skill, and labour-intensive industries—such as agriculture, construction, logistics, hospitality, and domestic services—where seasonal, temporary, and informal contracts are prevalent. These sectors are also characterised by higher turnover, weaker enforcement of employment protection, and greater exposure to cyclical fluctuations. As a result, migrant workers' labour market trajectories may differ systematically from those of natives, not only in levels (e.g., lower average earnings and higher unemployment risk) but also in the structure of transitions between labour market states. This raises the question of whether the same latent types identified in the U.S. framework—alpha, beta, and gamma—manifest similarly in the Italian context, or whether institutional segmentation and the concentration of migrants in secondary labour market segments produce distinct forms of employment instability.

Moreover, analysing Italy provides an opportunity to disentangle how much of the observed heterogeneity in employment dynamics stems from individual factors (e.g., human capital, search ability, or legal status) versus structural features of the labour market (e.g., dual employment protection, sectoral composition, and informality). The period 2009–2020 also spans several major economic and policy shocks—the global financial crisis, the sovereign debt crisis, and the pre-pandemic recovery—that differentially affected various worker groups. Investigating how these shocks interacted with labour market segmentation and migration patterns can shed light on the persistence of employment instability and the barriers to upward mobility in Italy.

By extending the alpha–beta–gamma framework to a setting characterised by strong institutional dualism and a large immigrant workforce, this paper contributes to understanding whether the patterns of latent worker heterogeneity documented in the U.S. reflect universal behavioural regularities or are mediated by country-specific institutions and compositional factors.

The analysis proceeds in two steps. First, we use longitudinal administrative data on worker flows to characterize heterogeneity in employment transitions. Following Gregory et al. (2025), we apply a grouped fixed effects (GFE) approach to classify workers into a small number of latent types based on their observed histories of employment, unemployment, and job-to-job transitions. This data-driven method captures persistent behavioural differences in search and match stability that are not explained by standard demographic or occupational controls. Second, we embed these empirical findings into a search-theoretic framework that allows us to interpret the estimated worker types in structural terms, i.e, linking differences in job-finding and job-loss rates to underlying productivity distributions, search intensities, and match quality dynamics.

By implementing this approach for Italy and by distinguishing between migrant and native workers, the paper seeks to shed light on three key questions. First, to what extent can the heterogeneity documented in the U.S., the existence of α, β, and γ workers, be observed in the Italian labour market? Second, are migrant workers disproportionately represented among the more fragile types, i.e., those with slow transitions into employment and unstable matches? Third, how do differences in the composition of worker types across groups contribute to aggregate unemployment fluctuations and to the persistence of inequality?

Answering these questions contributes to several strands of literature. The first is the macro-labour literature that studies cyclical fluctuations in unemployment and employment using search and matching models (e.g., Pissarides, 1985; Mortensen and Pissarides, 1994; Shimer, 2005). By explicitly incorporating heterogeneity in workers' employment dynamics, this paper provides new empirical evidence on the micro foundations of unemployment persistence. Second, it contributes to the growing literature documenting the role of latent heterogeneity in job transitions (e.g., Hall and Kudlyak, 2019; Ahn and

Hamilton, 2020; Morchio, 2020), extending this evidence to a Southern European labour market with distinct institutional and contractual features. Third, it relates to research on labour market segmentation and migration, which emphasizes the barriers migrants face in accessing stable employment and the persistence of dualism in Southern Europe (e.g., Boeri, 2011; Bentolila et al., 2012; Dustmann et al., 2016).

The findings have broader implications for understanding inequality and labour market integration. If migrants are more likely to belong to the less stable γ-type group, this would suggest that observed gaps in earnings and job security are not only the result of observable skill differences or discrimination, but also of deeper structural and institutional factors that govern match formation and persistence.

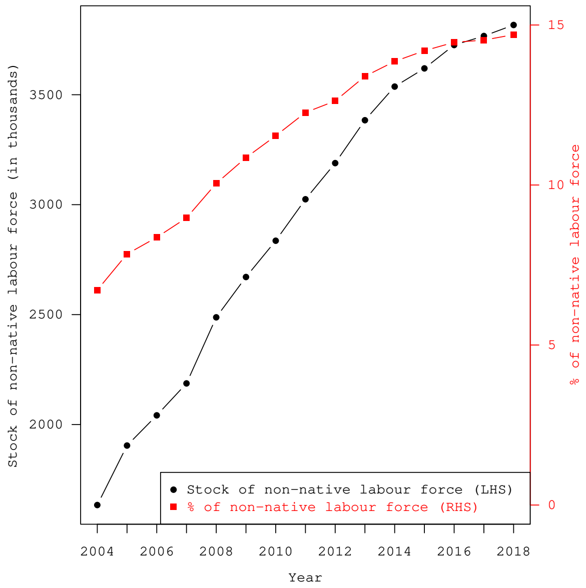
Finally, this research complements ongoing comparative studies applying the α–β–γ classification to different national contexts (e.g., Spinella, 2022; Darougheh and Lundgren, 2022; Castro et al., 2024). The Italian case adds a further dimension by explicitly considering migrant status, thereby connecting the literature on heterogeneous workers and macro-labour fluctuations with that on migration and segmentation.

The rest of the paper is structured as follows. Section 2 describes the institutional background and Section 3 illustrates the data sources used for the analysis. Section 4 presents the empirical methodology used to classify workers into latent types. Section 5 reports the results and compares the composition and employment dynamics of migrants and natives across types. Section 6 embeds the empirical findings into a search-theoretic model calibrated to the Italian labour market and discusses its implications for unemployment fluctuations and inequality. Section 7 discusses the limitations of this approach and Section 8 concludes.

2 The Italian labour market

The size of the non-natives labour force in Italy increased significantly from approximately 6% in 2004 to 15% in 2017 (Figure 1). The great majority of non-natives are low-skilled, and their share in the workforce has increased by approximately 15% in the period 2004-2018. The share of non-native high-skilled employees has increased by 2% only in the period considered.

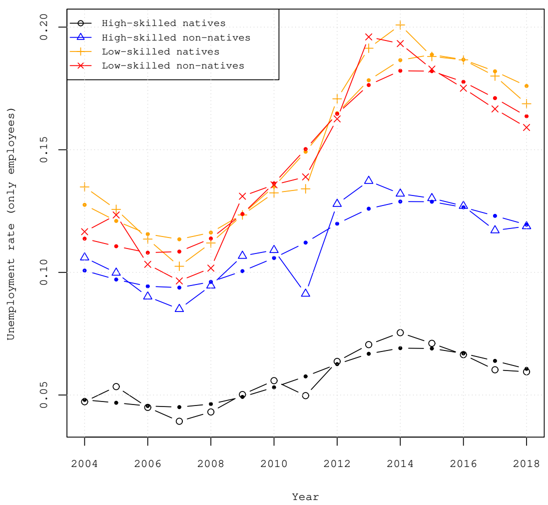
Figure 1. Non-native stock and share.



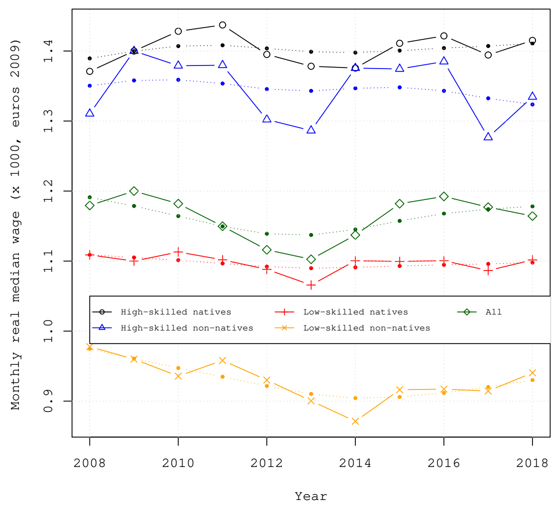
Source: Own calculations based on the Italian Labour Force Survey for the years 2004-2018.

There was a strong heterogeneity in wages, job creation and job exit rates among high-skilled, low-skilled, native and non-native employees. Among low-skilled employees, the unemployment rate is similar between natives and non-natives, while among high-skilled employees the unemployment rate of non-natives is much higher compared to the unemployment rate of natives (Figure 2a). After the 2008/2009 crisis, the unemployment rates of low-skilled employees have increased relatively more compared to the unemployment rates of high-skilled employees, both among natives and non-natives. Figure 2b reports the median (net) real wages of employees by skill level and country of origin (natives and non-natives) for the years 2008-2018 calculated using data from the Labour Force Survey as provided by the National Institute of Statistics (ISTAT). The real mean and median wages of both high-skilled and low-skilled native employees are higher than those of non-native employees, although the gap between the two is much larger among low-skilled employees. Specifically, employees with a low skill level who are non-natives earn 20% less than natives. Employees with a high-skilled level who are non-natives earn 10% less than natives. Native high-skilled employees earn 40% more than native low-skilled employees. Non-native high-skilled employees earn 55% more than non-native low-skilled employees. While the real wages of high-skilled employees, both natives and non-natives, has been approximately constant during the period considered, from 2009 to 2014 the wage level of low-skilled employees has decreased in absolute terms. The wage of non-native employees has decreased more than the wage of native employees, and although it increased after 2014 it did not reach the pre-crisis level.

Figure 2. Labour market indicators by worker type.

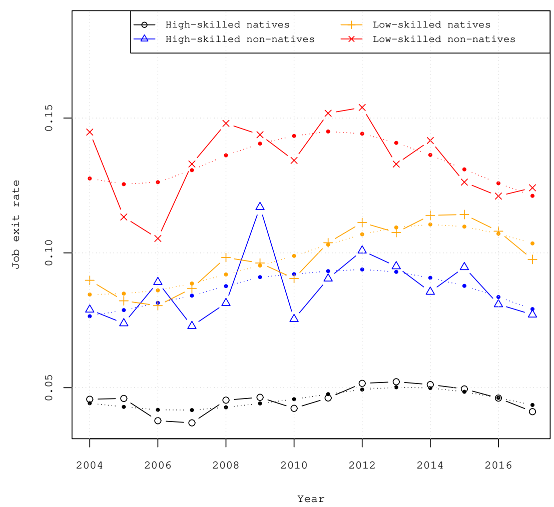


(a) Unemployment rate



(b) Median wages

(c) Job finding rate



(d) Job exit rate

Figure 2c reports the probability for an employee to find a job and the probability to lose a job, using the methodology proposed by Shimer (2012) and data on unemployment rates by skill level. High-skilled employees exhibit higher job finding rates and lower job exit rates compared to low-skilled employees, in agreement with the literature which provide evidence of low-educated employees having the highest gross mobility (turnover) compared to middle and high-educated employees (Landesmann et al., 2015). As in Dustmann et al. (2010), we find that among high-skilled, natives exhibit higher job finding rates, particularly after 2011, while among low-skilled employees, the opposite is true. Over time, job finding rates across all types of employees have crashed in 2011 as a result of the crisis, and while they have increased afterwards, as of 2018, they have not reached the level pre-crisis. Non-native employees tend to have higher exit rates. This is in line with the literature, which shows that non-native employees lose their jobs more often than natives but once being unemployed they have more probabilities of finding a job than natives (Barth et al., 2012; Fullin, 2011).

3 Data

In this study, we utilise the *Comunicazioni Obbligatorie* administrative dataset, which provides comprehensive records of a sample of job-to-job transitions of workers in Italy between 2009 and 2020. These data, collected by the Italian Ministry of Labour, detail mandatory notifications that employers submit regarding any hiring, contract change, termination, or transfer of dependent workers. The dataset includes unique identifiers for individual workers, enabling us to track entire employment histories over time and observe transitions between jobs, sectors, and contract types. Each record contains detailed information on the worker's demographic characteristics, occupation, employer, employment contract type (e.g., permanent, temporary, apprenticeship), contract start and end dates, and location.

Our dataset captures dependent employment relationships in both the public and private sectors within Italy but excludes self-employment. The granularity of employment spell data supports the analysis of job mobility patterns and labour market dynamics at daily frequency.

Following Gregory et al. (2025) and to focus on individuals with strong labour force attachment, we exclude from our sample all workers who have a gap of more than two years between consecutive employment episodes.

To mitigate issues related to labour force entry/exit and censoring, we define a two-year window at the beginning (2009–2010) and end (2019–2020) of the sample period.

If an individual is employed in the first quarter of 2009, we can accurately determine whether their job lasts more than two years (the highest duration bin used) or ascertain its start date based on the early window. Records for such individuals begin at the start of their job. Conversely, if an individual is unemployed in the first quarter of 2009 and their unemployment spell is shorter than two years, we begin their record at the start of that spell. If it exceeds two years, we start tracking from their first observed job in the period, assuming out-of-labour force status prior. Symmetrically, at the end of the reference period, if a worker is employed in the last quarter of 2018, we know if their job extends beyond two years or its end date. Records end with the job's conclusion. For those unemployed in that quarter, we determine whether their spell duration warrants stopping the record at the job or unemployment spell endpoint. After establishing the start and end date of each spell for each individual, we measure job duration as the number of months an individual is employed with a given employer, and unemployment duration as the number of months with no employment.

We summarise each individual's employment transition patterns by constructing the following statistics:

- The fraction of jobs lasting (a) less than 1 quarter, (b) 1–4 quarters, (c) 4–8 quarters, and (d) more than 8 quarters;
- The fraction of unemployment spells by corresponding duration bins;
- The total quarters of unemployment as a fraction of observed quarters on record;
- The total number of distinct jobs as a fraction of observed quarters;
- An "entropy" measure: the number of employment status changes per unit time ("switching rate").

These statistics provide a detailed profile of each individual's work history, including the distribution of job and unemployment durations, overall unemployment incidence, frequency of direct job-to-job transitions, and overall labour market fluidity.

4 Methodology

We discretise workers' heterogeneity in employment transition patterns using the k-means algorithm, a standard technique in the machine learning literature (Friedman et al., 2017), increasingly adopted in economics (Bonhomme et al., 2019, 2022). The k-means algorithm groups individuals into types according to their similarity across a set of employment and unemployment statistics. The optimal number of types, k, is selected via the cross-validation procedure of Wang (2010).

Let i index individuals in our sample. For each individual i, we construct a set of summary statistics:

- $s_{1,i}, s_{2,i}, s_{3,i}, s_{4,i}$: the fractions of jobs lasting (a) less than 1 quarter, (b) between 1 and 4 quarters, (c) between 4 and 8 quarters, (d) more than 8 quarters.
- $s_{5,i}, s_{6,i}, s_{7,i}, s_{8,i}$: the fractions of unemployment spells lasting (a) less than 1 quarter, (b) between 1 and 4 quarters, (c) between 4 and 8 quarters, or more than 8 quarters.
- $s_{9,i}$: the fraction of time spent in unemployment.
- $s_{10,i}$: the number of jobs per unit of time.
- $s_{11,i}$: switching rate.

All statistics are expressed as ratios standardised by their population-wide standard deviation. The statistics describing job duration are assigned a weight of 1/4 each, those describing unemployment duration a weight of 1/4 each, and the remaining statistics a weight of 1.

Given a number of types k, we denote an assignment of individuals to types by a map $C(i) \in 1, \ldots, k$. The algorithm solves:

$$\min_{C(\cdot)} \sum_{t=1}^{k} \sum_{i:C(i)=t} \sum_{j=1}^{9} w_j (s_{j,i} - \bar{s}^*_{j,t})^2 \tag{1}$$

subject to:

$$\bar{s}^*_{j,t} = \frac{\sum_{i=1}^{N} \mathbf{1}[C(i)=t] s_{j,i}}{\sum_{i=1}^{N} \mathbf{1}[C(i)=t]} \tag{2}$$

where $\bar{s}_{j,t}$ is the mean of statistic j in type t, and w_j is the assigned weight.

The k-means algorithm is iterated as follows:

1. Initialize: pick a dimension (statistic), rank individuals on this dimension, and equally split into k types.

2. Compute type means $\bar{s}^{(0)}j,t$ for each type.

3. At iteration m, assign each individual to the type whose mean vector is closest in squared weighted Euclidean distance, using means $\bar{s}^{(m-1)}j,t$.

4. Update type means, and repeat until type assignments converge.

5. To check for uniqueness, we repeat using different initial dimensions.

To determine the optimal k, we use the cross-validation method of Wang (2010): we partition the sample into three subsamples (two training, one validation). We estimate type means on both training subsamples, use these means to assign types within the validation subsample, and select k to minimise disagreement in type assignments within the validation set.

5 Results

We identify three distinct worker types in our sample (Tble 1). The majority (type α) are characterised by short unemployment durations and long job durations. Type γ workers are more likely to have short unemployment spells and jobs, while type β workers are most likely to experience long unemployment and short job spells.

Overall, type α workers are likely to find jobs quickly and retain them for extended periods. Type γ workers' transitions are less stable, and type β workers experience frequent unemployment and short job spells. The classification is highly persistent over time: about 90% of individuals retain their assigned type when reclassified with data from a different period, in line with findings from other countries ((Spinella, 2022; Darougheh and Lundgren, 2022).

6 The Model

To be written

Table 1. The three clusters on the base of the partitioning characteristics

Cluster	α	β	γ
Employment Q1	0.12	0.27	**1.94**
Employment Q2-Q4	0.19	0.30	**3.25**
Employment Q5-Q8	0.10	0.13	**0.47**
Employment Q9	**1.09**	0.02	0.28
Unemployment Q1	0.18	0.08	**2.28**
Unemployment Q2-Q4	0.20	0.13	**2.51**
Unemployment Q5-Q8	0.11	0.06	**0.52**
Unemployment Q9	0.85	**1.31**	0.81
Percentage unemployment	0.40	**0.90**	0.49
Average number of jobs	1.50	0.72	**5.95**
Volatility	0.02	0.01	**0.09**
Composition	0.34	0.56	0.11

7 Limitations

First, there is an implicit assumption that all nonemployment observed among "gamma" workers is involuntary and driven exclusively by job-search frictions. Some of these nonemployment spells may reflect voluntary nonparticipation decisions, such as temporary withdrawals from the labour force or preferences for leisure; distinguishing between these explanations is crucial for interpreting the results. A possible validation would involve the classification of worker types using micro-level longitudinal data that include information on search behaviour, which could help identify whether "gamma" workers actively seek employment when not working.

Second, there is no consideration of life-cycle considerations. Because mobility, employment stability, and transitions between employment and nonemployment vary systematically with age, failing to control for life-cycle patterns could lead to misclassification or exaggeration of the "gamma" share of the population. Treating the same behavioural criteria as applicable to both young and older individuals may overlook the fact that younger workers naturally experience higher turnover rates. Age should be incorporated more explicitly, for instance by comparing moments (such as employment duration or number of spells) across narrower age bands.

Third, the paper does not exploit wage information when identifying worker types or validating the model, even though the underlying theoretical structure resembles a job-ladder model. In such models, wage dynamics and match quality are intimately linked, so excluding wage data misses a critical dimension of heterogeneity. Rogerson recommends analysing whether employment transitions differ systematically across types in terms of associated wage growth, and whether the model reproduces the observed wage–tenure relationships.

Fourth, the paper conflates heterogeneity in productivity with heterogeneity in frictions. Standard search models predict that lower-productivity workers will experience both lower job-finding and higher job-separation rates even without additional frictions. Therefore, failing to control for productivity differences—e.g., by conditioning on education or demographic characteristics—makes it difficult to interpret the estimated heterogeneity as reflecting search ability or job retention skills.

Fifth, the analysis attributes all heterogeneity to workers, neglecting the possibility that some of it may stem from job or firm heterogeneity. Some jobs may simply be less stable than others, and certain workers may disproportionately match with those less durable positions. Incorporating two-sided heterogeneity—across both workers and firms—would provide a more realistic and policy-relevant understanding of labour market dynamics.

Finally, rather than beginning with a representative-agent search model and progressively adding dimensions of heterogeneity, an alternative approach would start directly from the data and use k-means clustering to classify workers into discrete "types." While this data-driven approach is innovative and avoids imposing parametric distributions, it also raises interpretive issues. The identification of types depends on a restricted set of moments (focused on transitions, excluding wages), and the authors do not apply the same classification algorithm to simulated model data, which would help evaluate how well the model replicates the empirical clustering. Moreover, the interpretation of sharply discrete types—alpha, beta, gamma—when most economic heterogeneity, whether in productivity, preferences, or job-search ability, is arguably continuous is questionable.

8 Conclusions

To be written

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Appendix

A Validation of Comunicazioni Obbligatorie (CICO) dataset for the analysis

A key question is how much our strategy in using the CICO dataset can take the true dynamics of Italian labour market.

We are interested to have the labour market status of employees and its change over time. In particular, we focus on unemployment and employment status, given the lack of information on the inactivity status. For reasons explained below, we restrict our attention to the active population conventionally defined as 15-64 years old individuals and among these only individuals with less than 24 months

Unemployed workers With respect to the actual unemployed workers, the individuals in the sample in CICO without a job:

- are overestimated because some of them could be inactive for demographic reasons (e.g. retired above 65);
- are overestimated because some of them who result unemployed for a long time (e.g. more than 24 months) are likely inactive individuals;
- are underestimated because some of them are in search of the first job (e.g. young individuals).

We check for the first two sources of bias taking only individuals in the range 15-64 and with a length of unemployment less than 24 months, but not for the third. This implies, for example, that the transition from school to work is not taken into account. Maybe this could also suggest excluding people under 25/30 years old.

Overall, the bias has an undefined sign, but after the two checks should be negative.

Employed workers With respect to the actual employed workers, the individuals in the sample in CICO with a job:

- are overestimated with respect to unemployed if we do not check for their ages;
- are underestimated if we have someone taking the job before 2009 and still on the job in 2020;

The first bias is checked by restricting the age of individuals, the second cannot be checked unless having a very long dataset.

Overall, the bias should have an undefined sign, but after the check, surely positive.

A.1 The entry in CICO

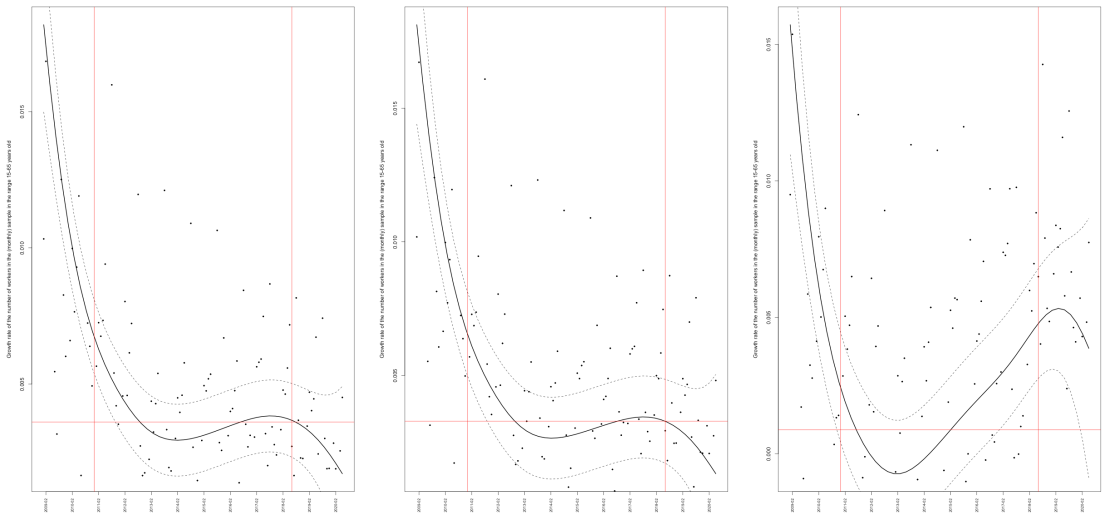

Figure 3. The rate of change of the number of individuals in the whole sample (on the left) versus a selected sample (in the center, 15-64 years old) versus a further selected sample (on the right, 15-64 years old and without a job for less than 24 months individuals). All statistics a re monthly base.

A.2 The unemployment rate from CICO

A.3 The flows of new and closed contracts in CICO

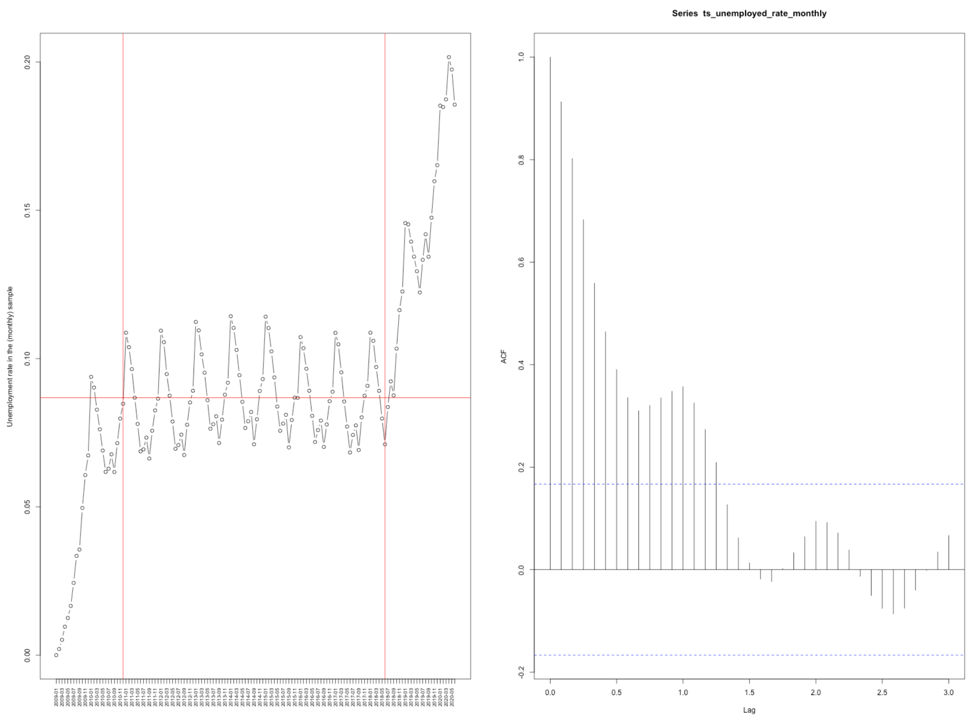

Figure 4. Unemployment rate based on CICO. Autocorrelation of unemployment rate.

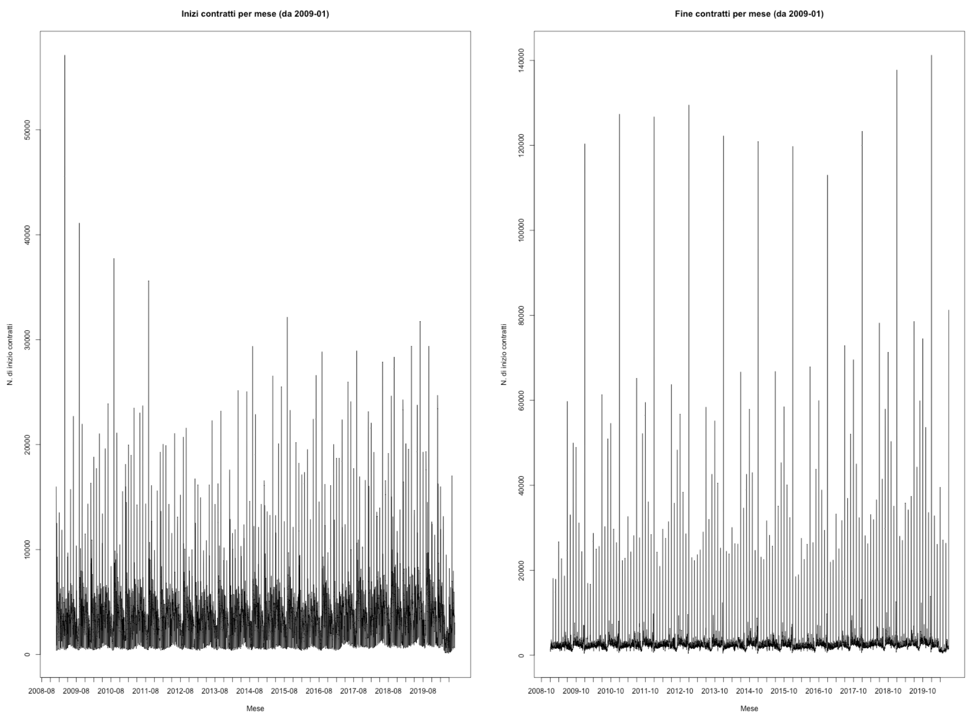

Figure 5. The number of new and closed contracts in the period 2009-2020.